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Research Article

Technology prioritization framework to adapt maintenance legacy systems for Industry 4.0 requirement: an interoperability approach

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Abstract

Paper aims: Aiming to avoid an inefficient digital transformation, the present work proposes a framework that will provide companies with a strategy to implement technologies to legacy systems of maintenance.

Originality: Such a framework was produced through a series of strategic analyses using multicriteria decision-making (MCDM) methods.

Research method: These analyses are composed of three steps. First, reviewing the literature of industry 4.0 and interoperability, combining the RAMI4.0 architecture and Framework for Enterprise Interoperability (FEI). Second, by exploring technics of maturity assessments, addressing systems attributes and requirements. Third, reviewing the literature of Total Productive Maintenance (TPM) and recent maintenance technologies applications.

Main findings: The results confirm that such a framework can support the adequacy of legacy systems that are part of digital transformation projects.

Implications for theory and practice: To test the proposed framework, a multinational industrial entity belonging to the automotive sector was selected for a case study.

Keywords

Industry 4.0. Industrial maintenance. Multicriteria Decision-Making (MCDM) methods. Interoperability. Digital transformation.

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1. Introduction

In the midst of a highly informational scenario, interoperability is an element to be explored by organizations. Such term represents the capacity of a system to communicate between two or more others, in order to use the shared data and access external functionalities (Chen & Daclin, 2006). Among the technologies that exert interoperability in manufacturing, the Internet of Things (IoT), Big Data, Artificial Intelligence (AI), Augmented Reality, Machine to Machine (M2M), Analytics, and Cloud Computing stand out (Alcácer & Cruz-Machado, 2019; Oztemel & Gursev, 2020). Classified as information and communication technologies (ICTs), they are the basis for Industry 4.0 (I4.0), enabling the emergence of cyber-physical systems. According to (Erasmus et al., 2020;

Sotnyk et al., 2020; Rüßmann et al., 2015) some of the benefits that such systems' networks have provided to organizations are increased productivity, alteration of the workforce profile, and increased competitive potential.

However, for an assertive implementation of those technologies, it is necessary that conceptual, technological, and organizational requirements are satisfied (Lamine et al., 2017). As the world experience a transition to the I4.0, recurrently many adaptations involve legacy systems. Papers such as (Batlajery et al., 2014) characterize these systems as those with high usage times, vital to the organization's business, however, do not fit into future IT strategies. Taking that into account (Borangiu et al., 2020; Sotnyk et al., 2020) shows that implementing a system with the maturity level necessary to operate in the Industry 4.0 scenario will require a digital transformation project.

Parallel, there is a problem with modernization not being prioritized by organizations, also similar for the maintenance sector, seen more as an inevitable necessity than as a goal to pursue (Pintelon & Parodi-herz, 2008). Equivalent to modernization, the role of industrial maintenance has become a strategic element to achieve business objectives (Cupek et al., 2019; Patalas-Maliszewska & Skrzeszewska, 2018). According to the literature, the maintenance goals involve *safety*, expressed through a higher reliability coefficient of equipment prone to critical failures; *availability*, when considering the time when the equipment is producing at full capacity; and *budget*, involving the reduction of maintenance costs (Deac et al., 2010). Those goals are related to the benefits provided by the I4.0 technologies (Cañas et al., 2021; Kozma et al., 2021).

Along these lines, the present work addresses the difficulty evidenced by digital transformation initiatives, underlined in legacy systems, and the proximity of modernization and maintenance to achieve business objectives. Notwithstanding, despite empirical evidence for the implementation and effects of I4.0 technologies is available in the literature (Wiech et al., 2022), digitalization related decisions are costly and require solid concepts for firms to initiate digital transformation (Chen, 2017). Further, it is understandable that every project must operate within a budget and time limit, therefore not all the functions of an I4.0 level system can be implemented rapidly and cost-effectively at once (Darko et al., 2020; Woodhead et al., 2018; Yu et al., 2021).

In the whole, focusing on the industrial maintenance area and based on an assessment of qualifying attributes of a given organization, the research developed here give guidelines to answer the following research question: "How to define a technology prioritization plan in order to adapt legacy systems for Industry 4.0 requirements?". This is done by stablishing a digital transformation framework with a set of models based on Multicriteria Decision-Making (MCDM) Methods. Therefore, they are used to integrate different domains (Interoperability, Maintenance, Legacy Systems adequacy, maintenance technologies in the industry 4.0 context) in a none isolated manner to define a non-trivial digital transformation strategy.

Next, section 2 will explain the scientific scenario and the theorical dimensions which are foundations to the proposed solution. Furthermore, section 3 explains the framework and section 4 discuss results of the framework application in a real case study. Finely, section 5 concludes and suggests improvements.

2. Scientific scenario and theoretical dimensions

Disruptive ICT's promote escalating industrial productivity, putting current economic models in check, fostering the growth of industrial organizations, change the profile of the workforce, and ultimately increase the competitiveness of companies (Rüßmann et al., 2015). Thus, the proximity with the term *interoperability* is evident because of the prominence of such technologies, which will increase the collaboration between systems, machines, and people; that way, enabling greater speed, flexibility, and efficiency in production processes, resulting in higher quality at reduced costs (Carvalho et al., 2018; Gallegos-Baeza et al., 2021; Kozma et al., 2021; Tao & Qi, 2019). Aiming this scenario, the research presented here proposes a series of MCDM methods, encapsulated as a framework, to support strategic decisions to adequate legacy systems to Industry 4.0. This is done focusing on interoperability. As result, technologies will be suggested for implementation, regarding the analyzed system's specificities and background in which it performs. Narrowing the range of technologies to be proposed, consequently being more assertive, this work highlights systems in the context of industrial maintenance. Figure 1 describes the connection between the research dimensions in this scientific scenario and the research's methodological sequence.

To fully understand how the framework works, its theoretical dimensions need to be addressed in the scenario of digital transformation. Following the research strategy, firstly, legacy systems are addressed. Then, RAMI4.0 architecture (Plattform Industrie 4.0, 2015) and Framework for Enterprise Interoperability (FEI) (Chen et al., 2007) are theories explored in the industry 4.0 and interoperability dimensions each. Finely, the maintenance dimension is specified and recent technologies applied into its modernization are addressed along with a referential model.

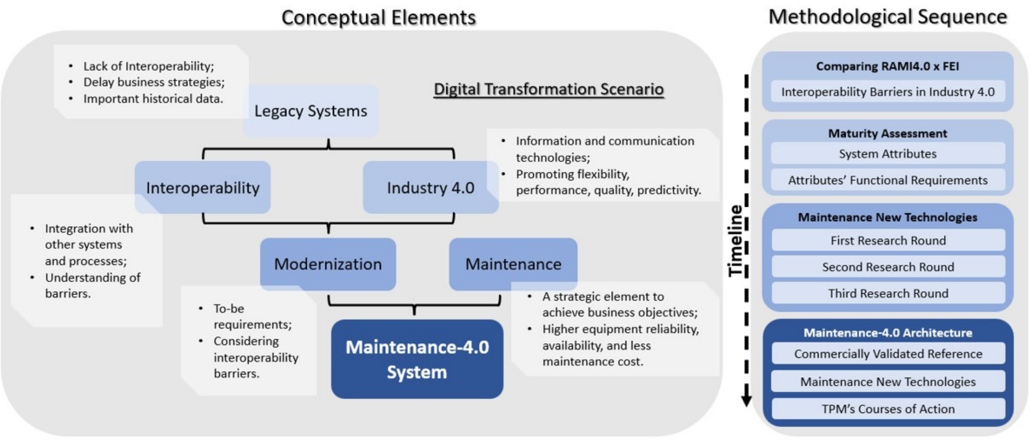

Figure 1. Research strategy.

2.1. Legacy systems dimension

Even after three decades of research in modernizing legacy systems, it is notable that many remain in operation. This is due to the fact that these systems are generally very comprehensive (Brooke & Ramage, 2001; Ramage, 2000). They interoperate with other processes or subsystems, only remain in operation due to their technical complexity of replacement and/or adaptation and criticality in the organization's operations, in such a way that remains in constant activity. Every system is likely to become a legacy at some point and its data is characterized as valuable since its history can be used to understand its behavior in search of optimization (Batlajery et al., 2014). However, to remain competitive, companies must continually change their processes, sometimes radically, and legacy systems can delay modernization processes and directly influence the company's business strategy (Liu et al., 1998; Matsumoto et al., 2020; Moeuf et al., 2018; Morariu et al., 2016).

2.2. Interoperability and Industry 4.0 dimensions

Two architectures were bases to allocate legacy systems into the conformities of I4.0 in a coordinated way. They adopt structures that organize evaluative attributes in perspectives that portray the adequacy of maintenance systems, considering their interoperability barriers.

The first, Framework for Enterprise Interoperability (FEI) (Chen et al., 2007), was considered by the premise that interoperability might be a relevant metrics to understand what can or cannot be implemented to a system. This possibility is feasible because FEI relates conceptual, technological, and organizational barriers linked between the enterprise layers, that could be generated by systems trying to communicate. Coupled with that, the prerogative that interoperability barriers could difficult the insertion of technology seems feasible once legacy systems and other adjacent systems/processes may share communication dependence.

The second is the Reference Architecture Model for Industry 4.0 (RAMI4.0) (Plattform Industrie 4.0, 2015), converging multi-stakeholder views on how I4.0 can be accomplished based on existing communication standards and functional descriptions (Pedone & Mezgár, 2018). Analogously to the FEI, the RAMI4.0 presents a similar enterprise's layers perspective. Considering that this research investigates interoperability barriers that might appear by implement I4.0 technologies in legacy systems, those frameworks were compared (see Figure 2).

This composition considers interoperability barriers into an I4.0 referential architecture. The following subsections explain, firstly, how this relation generated a maturity As-is view of a legacy maintenance system, and after, how Industry 4.0 technologies could enhance that system, expressed in a To-be view.

2.2.1. System maturity for Industry 4.0

The authors propose a maturity view through the lens of RAMI4.0/FEI architecture in early studies. It aims to understand maintenance systems' maturity by the relations between its attributes and functional requirements (Cleland-Huang, 2007). The present work defines Attribute as something that qualifies a concept, in this case, maintenance. The definition adopted for Functional Requirement is something that supports the Attribute to which it is related. Figure 3 illustrates how these elements are related to each other.

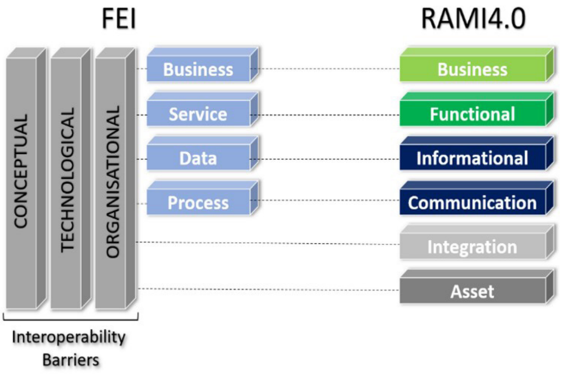

Figure 2. FEI barriers x RAMI4.0 layers compared frameworks.

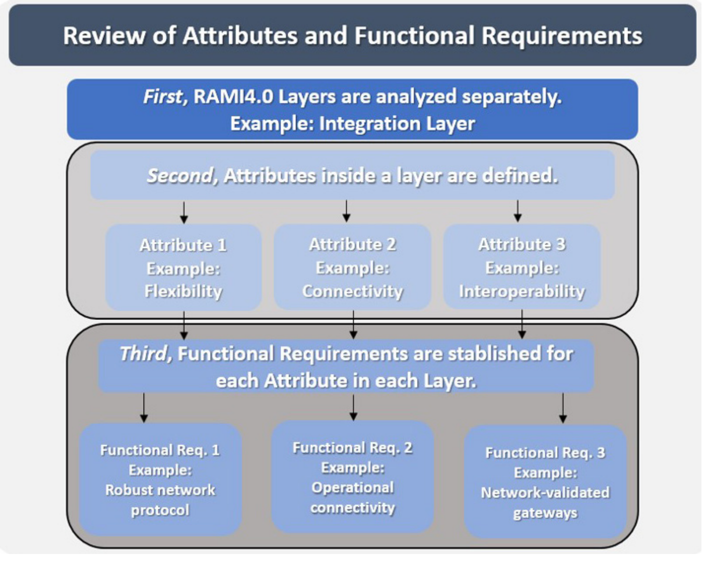

Figure 3. Relation between attributes and functional requirements.

The purpose of the attributes is to qualify maintenance within the RAMI4.0 layers. Using the Assets layer as an example, the attributes raised have a bias to guarantee the functionality of the acquisition system and to ensure the quality and the way that the sensing in the equipment is carried out. In the case of functional requirements, they must support the attributes, so that they are met. Again, using the Asset layer as an example, the functional requirements are related to the needs of a good sensing system, what should be sensed and what these sensors should monitor. Table 1 presents all 25 attributes raised in the literature and their descriptions, follow by the 62 functional requirements derived from the attributes, therefore using the same literary base indicated by the ID column.

2.3. Maintenance and modernization dimensions

The legacy systems addressed in this work were constrained to industrial maintenance. Maintenance is currently seen as a complex management process that combines several organizational processes, such as production, quality, environment, risk analysis, and safety. Bearing in mind that nowadays maintenance management is a key part of the organizational composition, it is important to keep its processes in line with the company's strategy. An appropriate maintenance strategy not only reduces the likelihood of equipment failure but also improves the working condition of the assets, resulting in lower maintenance costs and/or higher product quality (Sipsas et al., 2016; Vaisnys et al., 2006). In an exploratory character, a partial review of the literature with three research rounds was carried out, focusing on recent technologies for the maintenance sector.

Table 1. Attributes and Functional Requirements description and its references.

Layer	ID. Attribute	Description	Functional Requirements	Reference
Asset	A1. Identify Functional Failures	When identifying and mapping the functional failures of the equipment, it is possible to establish what are the possible parameters that indicate these failures. - Establish abnormal conditions.	- Interpret the relevant parameters in the equipment;	(Kumar et al., 2018)
	A2. Equipment Health	Monitoring the health status of the equipment employs sensors within the structure of the equipment (such as motors, tracks, bearings, etc.) monitoring and providing predictions about the current state. - Supervise equipment performance.	- Preserve equipment integrity in data acquisition;	(Wang et al., 2017)
	A3. Reliability in Data Acquisition	If acquired reliably, the information has potential value, both to create a historical database and to discover patterns and relationships between parameters. - Compare purchases with models and standards already specified.	- Perform the monitoring of several parameters in parallel;	(Karim et al., 2016)
	A4. Telemetry	In maintenance, there is a tendency for all equipment to have more embedded electronics and monitoring through the same of its main subsets. - Guarantee up-to-date information in the monitoring of data.	- Quality and properly installed sensors;	(Furch et al., 2018)
Integration	A5. Connectivity	Wireless sensor networks (WSNs) can provide a lot of useful data and are being used more and more in the scope of maintenance. - Ensure an adequate data transmission rate; - Certify the reach of the required communication band.	- Use robust network protocols;	(Botta et al., 2016)
	A6. Security / Stability	Even with the demand for connected elements increasing, it is necessary to ensure continuous operation. - Use confirmation protocols; - Encrypt data transmitted by gateways.	- Operational reliability;	(Santos et al., 2009)
	A7. Flexibility	Gateway devices require a high level of flexibility, allowing hardware to be integrated into the network. - Connected elements have knowledge about other elements connected to the network.	- Devices with updated firmware;	Wintrich et al., 2015)
	A8. Interoperability	Maintenance systems must be able to communicate and exchange information. - Use gateways validated by networks; - Use data access middleware for direct connectivity between apps and databases.	- Allow the ability to connect with different industrial protocols;	(Karim et al., 2016)
Communication	A9. Security and Privacy	With the increasing usability of technologies such as Cloud, concerns arise such as network security, suppliers and leakage of sensitive information to the company. - Properly designed access authorization policies.	- Ensure access control of devices;	(Botta et al., 2016)
	A10. Mobility	In the scope of maintenance, technological mobility plays an important role in making information accessible. - Interactivity and operability in real time.	- Allow connection and exchange of information on mobile devices;	(Muller et al., 2008)
	A11. Data Source Heterogeneity	Predictive maintenance requires an efficient data management system from a variety of devices. - Adjust data at different levels; - Allocate services and applications in different layers.	- Relate different types and cloud architectures;	(Botta et al., 2016)
	A12. Scalability	Important feature in the communication system, which indicates how many active elements in the system the network can support. - Limit the number of requests over the network at a time.	- Use protocols that allow the unique identification of elements on the network;	(Botta et al., 2016)
Information	A13. Speed	To maintain the efficiency of maintenance systems, it is necessary to ensure the speed and proactivity of the system's information flow. - Check the ideal data processing speed; - Use point-to-point connections between the database and the applications.	- Design architectures that balance data latency, requirements and decision cycle;	(Laney, 2001)
	A14. Volume	A network with multiple sensors (WSNs) relies heavily on having robustness to store data about maintenance. - Reduce certain analytical structures to a percentage of statistically valid sample data; - Monitor data usage to identify unused information and discard it.	- Ensure data storage capacity;	(Laney, 2001)
	A15. Variety	The variety refers to the range of type and data sources. Along with Speed and Volume, they are the 3Vs in a system that operates with information. - Create a data profile to resolve inconsistencies and discover data relationships.	- Establish a filter to avoid repetition of data;	(Laney, 2001)
	A16. Utility	The information about the equipment should have an influence and be useful in the results of the maintenance analysis. - Guarantee the quality of the recorded information; - Filter the information to make it more useful and accurate.	- Interpret and map only the important parameters in the equipment;	(Schmidt et al., 2017)
	A17. Data Fusion	Merging data is a prerequisite to obtain data inference when handling a maintenance system, with multiple sensors and different data sources. - Ability to prioritize and differentiate data; - Create data models about maintenance and compare them.	- Preventing data overload;	(Welz et al., 2017)

Those maintenance attributes and functional requirements give the present work directions in how to analyses maintenance systems in an a priori state (i.e., As-is).

Table 1. Continued....

Layer	ID. Attribute	Description	Functional Requirements	Reference
Functional	A18. Diagnosis	The diagnosis has the objective of detecting the irregularity, and providing information about its origin and severity. Diagnosis is an important factor in the assertiveness of decision-making. - Create a database with a history of failures and monitoring of equipment health; - Define the tasks to be performed and the time spent based on the state of the equipment.	- Identify deficiencies in the process;	(Yam et al., 2001)
	A19. Intelligence	Systems need to evolve in automatic fault detection, acquiring learning based on fault history. - Use hybrid intelligent systems that learn to identify and predict anomalous situations.	- Improve the accuracy of the algorithms that reproduce human decision-making;	(Yokoyama, 2015)
	A20. Efficiency	The maintenance system should improve compared to past maintenance histories. - Record failure prediction learning based on maintenance history; - Optimize the proactivity of real-time information integration.	- To assimilate several parameters and indicators to strengthen the confidence of the result;	(Baidya & Ghosh, 2015)
	A21. Results View	The results should be presented in a practical and detailed way to assist the decision maker. - Present diagnostics in a friendly and intuitive way to those responsible.	- Present fault characteristics, monitored parameters, possible causes and mapping of all maintenance steps;	(Efthymiou et al., 2012)
Business	A22. Availability	Predictive maintenance should ensure greater availability of equipment, reducing machine downtime. - Use the information correctly to avoid uncertain machine stops.	- Use downtime indicators to define maintenance planning and scheduling;	(Jantunen et al., 2011)
	A23. Resources	The availability of the resources used needs to be made in a timely manner, otherwise efficiency will be lost and the equipment unavailability gaps will increase. - Early availability of the necessary tools based on the predictions made; - Explore mobility solutions to facilitate the performance of tasks regarding maintenance.	- Have a specialist with know-how in predictive maintenance to regulate the appropriate combination of technologies;	(Behera & Sahoo, 2016)
	A24. Decision-making	The assertiveness in knowing which is the best decision to face a failure and the time to do it is one of the main points in the field of predictive maintenance. - Use of statistical tools to support decisions; - Assist in an easy and quick way in individual decision making.	- Provide and structure information about the problems encountered;	(Yam et al., 2001)
	A25. Costs	Today maintenance is considered a cost center for the company, being necessary to evaluate the investment of the implementation with indicators such as ROI for example. - Optimization with intelligent methods of resource sharing.	- Strategically assess the feasibility of implementing the necessary technologies;	(Jantunen et al., 2011)

Those maintenance attributes and functional requirements give the present work directions in how to analyses maintenance systems in an a priori state (i.e., As-is).

2.3.1. First research round

The first research round provided a general context of I4.0 technologies. For that, the most cite reports with frameworks already formalized in the literature were used (see Table 2).

The objective was to gain an overview of I4.0 technologies, with the perspective of different technology consultancies.

Table 2 Technology consultancies and its reports.

Consulting Companies	Report
(Capgemini Consulting, 2014)	Industry 4.0 - The Capgemini Consulting View
(Deloitte, 2015)	Industry 4.0: Challenges and solutions for the digital transformation and use of exponential technologies
(PWC, 2016)	Industry 4.0: Building the digital enterprise
(PWC, 2015)	The Smart Manufacturing Industry
(Cisco, 2015)	The Digital Manufacturer Resolving the Service Dilemma
(McKinsey & Company, 2016)	Industry 4.0 at McKinsey's model factories
(Rüßmann et al., 2015)	Industry 4.0
(Acatech, 2017)	Industrie 4.0 Maturity Index
(Roland Berger, 2014)	The Digital Transformation of Industry
(Plattform Industrie 4.0, 2015)	Plattform Industrie 4.0
(The Warwick Manufacturing Group, 2017)	An Industry 4 readiness assessment tool

2.3.2. Second research round

In the second round, results from the overviewed technologies were validated in academic articles, focusing on its solutions for the maintenance sector. This research round was conducted as follow: (i) was searched the relation between "technology" AND "maintenance" (e.g., Cloud AND Maintenance; or, Augmented Reality AND Maintenance); (ii) only open access articles were searched; (iii) period from 2014 to 2019 was considered mature since the term "Industry 4.0" appeared by 2011 (Rojko, 2017). The most open access research platforms used at the time were: ScienceDirect and Archive Ouverte HAL. At the end, 58 articles were considered.

2.3.3. Third research round

Finally, in the third round, the technologies highlighted for the industrial maintenance were filtered and allocated into groups. The whole literature database ended with 69 articles and reports. From it, nine Maintenance-4.0 technology groups were identified: Big Data, Analytics, Artificial Intelligence and Cloud Computing, formalized as cyber-physical subgroup; Advanced Machines, Advanced Materials, Flexible Connection Devices and Digital-to-Real Representation (i.e., encapsulating Digital Twin applied in maintenance activities), formalized as application subgroup; and Sensors (i.e., encapsulating IoT and Smart Sensors, formalized as the bridge to digitalize physical operations). Table 3 details each group.

Table 3. Maintenance-4.0 technology groups, characteristics and applications.

Technology Group	Characteristics/Applications
Analytics	Predictions, data processing, historical data analysis, troubleshooting, increasing the effectiveness of operational planning, performance forecast, quantum computing, and knowledge support system autonomous actions;
Artificial Intelligence	Machine learning techniques, auto optimization, automatically learn, interaction with the physical environment, predict regarding prognostic decision-making, enabling maintenance-aware and automation of production process and interpolation;
Big Data	Data warehousing, data mining, dataset, vibration/temperature data, condition/state data, data-driven model, life-cycle data, control systems data repositories, data-driven algorithm, statistical process control (SPC) data, and raw historical data;
Cloud Computing	Network connection extension, remote operable software, platform between customers and suppliers, data exchange area, heterogeneous network devices, CMMS may be an add-on or an integrated part, data supply chain and sensor networks;
Advanced Machines	Environment whereby smart machines that can communicate with one another (m2m communication), human-machine-interaction, self-healing equipment, high-performance laser beam, autonomous robots, A.I. applied in machines, collaborative and proactive machines, machines interaction with physical objects, connectivity with the factory and real-time feedback/communication;
Advanced Materials	Examples of that are data monitored components towards nanotechnology and self-healing materials. Replaceable component, resistant to external ambient/influences and aging, spread part production, cleaning components, nanotechnologies, and self-repairing materials;
Flexible Connection Devices	Smartphones, real-time transmission of analyzed object status, machine status input, check products status and track them, human-machine interaction and CMMS control device;
Digital-to-Real Representation	Augmented reality googles, assistance with localization and diagnostics of faults in the system, remote maintenance/inspection, virtual reality simulation training, and visualization of prototypes;
Sensors	Data gathering/transmitting physical components, equipment containing an RFID tag, condition monitoring processes, real-world scanning, vision/sound/temperature sensitivity, wireless sensors, alert on equipment maintenance need, and remote detection.

2.4. Maintenance-4.0

Various concepts have been developed to increase maintenance effectiveness. One of the most commonly used concepts in organizations around the world is Total Productive Maintenance (TPM). The TPM emphasizes proactive and preventive maintenance to maximize the operational efficiency of the equipment. Production losses, together with indirect and hidden costs, make up the bulk of the total production cost (Kodali et al., 2009). Developed to support TPM initiatives, Overall Equipment Effectiveness (OEE) is a metric that identifies the percentage of planned production time that is truly productive. The OEE loss of availability, loss of performance, and loss of quality can be subdivided into what is commonly called TPM Six Big Losses (Vaisnys et al., 2006), the most common causes of lost productivity in manufacturing.

In order to achieve I4.0 adequacy for the maintenance sector the six big losses were considered (Ahuja & Khamba, 2008). For those losses, the model in Figure 4 formalizes *courses of action*, meaning that for each loss there is a course of action based on an I4.0 solution.

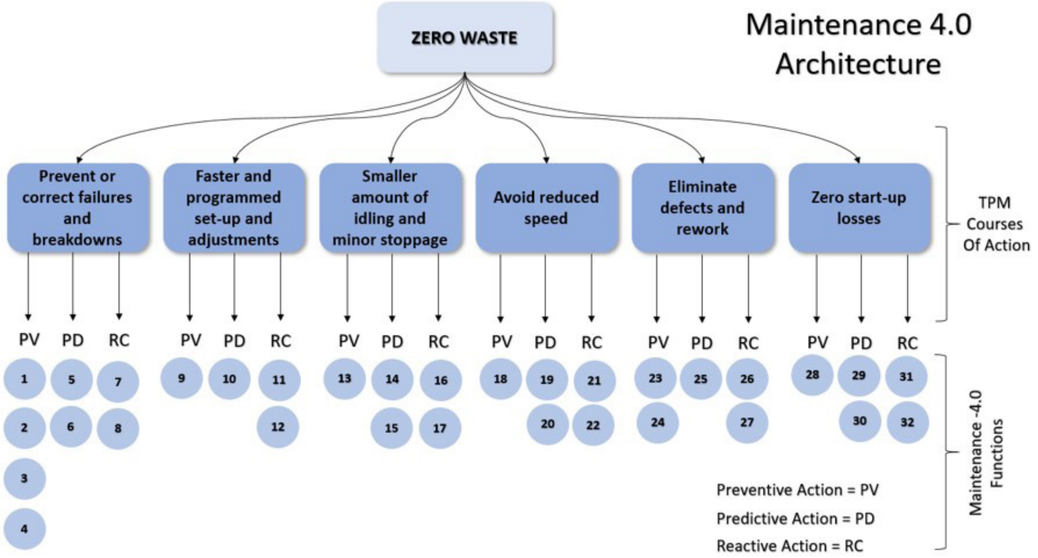

Figure 4. Maintenance-4.0 referential model based on TPM.

Such referential architecture was based on a digital asset management platform. With operations in more than ten countries and more than 15 years of know-how in the maintenance area, it can be considered a commercially validated source, reliable in defining applications. Because the scientific literature varies widely from organization to organization, this platform was chosen as a tool to define maintenance in Industry 4.0. Moreover, those courses of action are categorized into three main maintenance approaches: predictive, preventive, and corrective (Dhillon, 2002). Therefore, the spheres, or Maintenance-4.0 functions, represent enablers for predictive, preventive, and corrective approaches based on the technologies reviewed in the previous section (2.3). The 32 functions are shown (ranked) as a product of the case study in section 4.

In resume, aiming to guide maintenance processes to *zero waste* using disruptive technologies, this proposed model serves as a To-be guide, for the presented As-is analysis (2.2.1), due to interoperability barriers. Alternatively, what is needed to implement (i.e., disruptive technologies) according to what is possible to be implemented (i.e., interoperability barriers).

2.5. MCDM

Not used as a theoretical dimension but as part of the scientific scenario in a tooling bias, multicriteria decision making/analysis (MCDM/A) methods emerged in the search for solutions to complex problems that are difficult to measure, already demonstrated in the maintenance domain (Ruschel et al., 2017). This strategy is used as tools for more assertive decisions in systems adequacy, also following a couple of referential researches which applies decision-making to assessment in the dimensions of interoperability and Industry 4.0 such as (Battirola Filho et al., 2017; Lazai Junior et al., 2020).

Four elements characterize MCDM methods: Set of "alternatives", from which the decision is chosen; set of "criteria", or factors related to making a good decision; the "preferences" of the decision-maker, being clear, the problem becomes more understandable; and the "result" of each choice, measured in terms of criteria according to the decision maker's preferences.

Two different MCDM are used for the three steps framework, detailed in the next section. For Step 01 and 02, the Analytic Hierarchy Process (AHP) (Saaty, 1987) is used in order to derive priorities based on sets of peer comparisons, thus it is structured on the intrinsic ability to ponder their perceptions or ideas hierarchically (Forman & Peniwati, 1998). This method uses a compensatory characteristic, weighting the positive and negative attributes of the considered alternatives and allowing positive attributes to offset the negative ones (Elbok & Berrado, 2020). This article also explores the AHP possibility to combine geometric means, thus, aggregating the decision-makers responses according to the approaches presented in (Ssebuggwawo et al., 2009).

In Step 03, the Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE II) is used. It is characterized as an interactive method designed to deal with quantitative, qualitative criteria, and discrete alternatives. This method can classify alternatives that are difficult to compare due to a commitment to standards of evaluation as non-comparable alternatives (Athawale et al., 2012). It suggests a non-compensatory strategy, eliminating alternatives that do not meet a particular criterion (Banihabib et al., 2017). According to (Brans & Mareschal, 2005) it have been applied in varied fields such as industrial locations, labor planning, investments, medicine, chemistry, tourism, and ethics.

Although the two methods applied are based on different strategies, they meet the evaluative requirements of each step of the proposed framework. Also, the use of a hybrid MCDA approach offers more robust results than isolated MCDA methods (Liou et al., 2017). The next section details the framework.

3. Framework

The framework proposed in this article is structured in three steps. In Step 01 the AHP method is used to assess the organization's maturity, relating the I4.0 attributes and requirements in a maintenance bias. Step 02 is also built for the application of the AHP method, which will provide the allocation of weights for functions of a Maintenance-4.0 referential architecture, giving a selection of the most needed ones. Finally, at Step 03, the PROMETHEE II method will be applied to prioritize the technologies that will best adapt to the functions selected in the previous step Figure 5.

It is expected that after applying the framework, a legacy maintenance system will have its main requirements highlighted, indicating what needs improvement according to I4.0 technologies. The decision analyses consider not only what needs to be implemented to improve the system but also what is feasible regarding interoperability barriers.

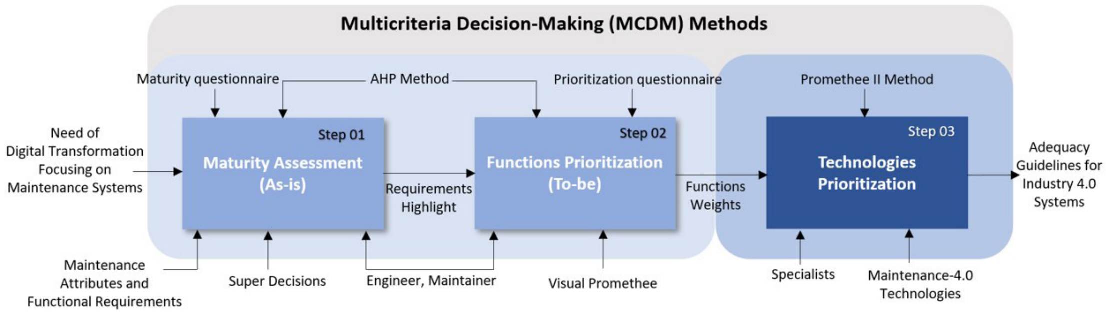

Figure 5. Framework overview.

3.1. Maturity assessment (Step 01)

Once is confirmed the organization's strategy to optimize its systems to an I4.0 scenario, in Step 01 an assessment of its maturity concerning the desired requirements is carried out. For this, engineers and maintainers who know in depth the maintenance processes and systems to be evaluated must be available, answering the proposed AHP model. They will be in the role of decision-makers. Figure 6 reflects such a model by constructing classification structures from the six layers of RAMI4.0/FEI. Working as a maturity assessment, this model describes the decomposition of a machine in its structured properties, enabling its virtual mapping.

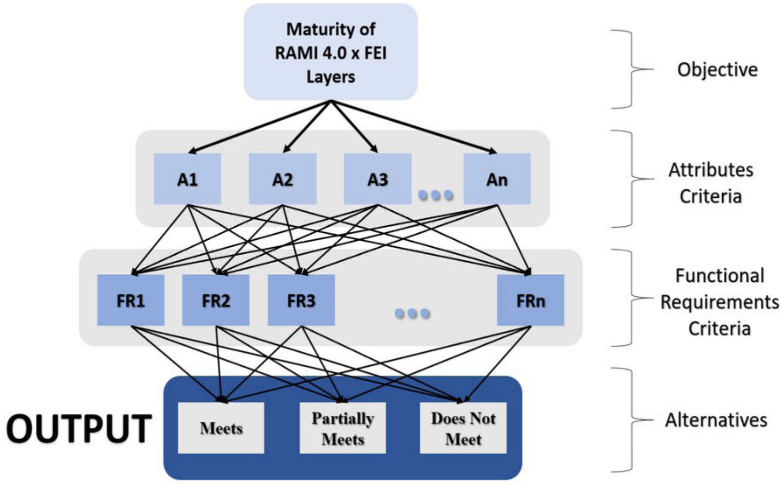

Figure 6. Step 01 – Maturity assessment (AHP model 1).

The name of the analyzed layer will be located at the top level of the decision model, representing the model's objective. The intermediate level will consist of attributes and functional requirements belonging to the industrial maintenance domain, distributed among the six layers to be analyzed. In the end, the lower level presents the alternatives: meets, partially meets, and does not meet; related to each functional requirement of the intermediate level. The relation attributes/requirements qualify the analyzed system (Justus et al., 2018).

Before this decision support method, a questionnaire aims to answer the importance (i.e., weight) of the elements to be raised. This is done based on the know-how of the chosen engineers and maintainers. Then, performing the AHP's peer review, the three alternatives are ranked, thus providing the result of the maturity assessment for each layer of RAMI4.0/FEI. When all six layers are evaluated, it will be possible to obtain the degree of maturity related to the requirements of Industry 4.0.

3.2. Maintenance-4.0 functions prioritization (Step 02)

Having delimited the areas with a major lack of industrial maturity in Step 01, the objective of Step 02 is to prioritize maintenance functions. Those functions will be parameters in the process of implement I4.0 technologies to the legacy systems analyzed. The AHP method will be used again, but in another model (see Figure 4), aiming to gather the functions' weights solely and not support a decision. In other words, this AHP model will be used for assigning weights to the functions according to the preferences of the decision-makers, not regarding alternatives, as done in the previous Step 01. After that, those weights will be used to support the last decision step.

At this stage, another questionnaire, now based on the Figure 7 model, reflects Maintenance-4.0 expectations. It presents decision-makers a series of maintenance functions and their application in the light of I4.0. Based on the TPM's six main losses, the engineers and maintainers must consider their decisions regarding predictive, preventive, and reactive approaches that will guide maintenance processes to zero waste. At the end of this step's comparison, each function of the Maintenance-4.0 model is ranked by weight.

3.3. Maintenance-4.0 technologies prioritization (Step 03)

Based on the maintenance functions weighted in the previous stage, Step 03 objective is the prioritization of I4.0 technologies that best suit those functions. Here, the decision model does not require the organization's engineers and maintainers, leaving the role of decision-maker to a maintenance-4.0 specialist. Considering it, the literature review on I4.0 technologies under the maintenance domain (section 2.3) serves as a base.

Step 03 decision model uses the PROMETHEE II method. The weights of each function of Maintenance-4.0, from the previous step, will be input and related to the nine technology groups from the literature review on maintenance technologies, as shown in Figure 8. The decision-maker is responsible for analyzing the technologies necessary to cover the maintenance functions.

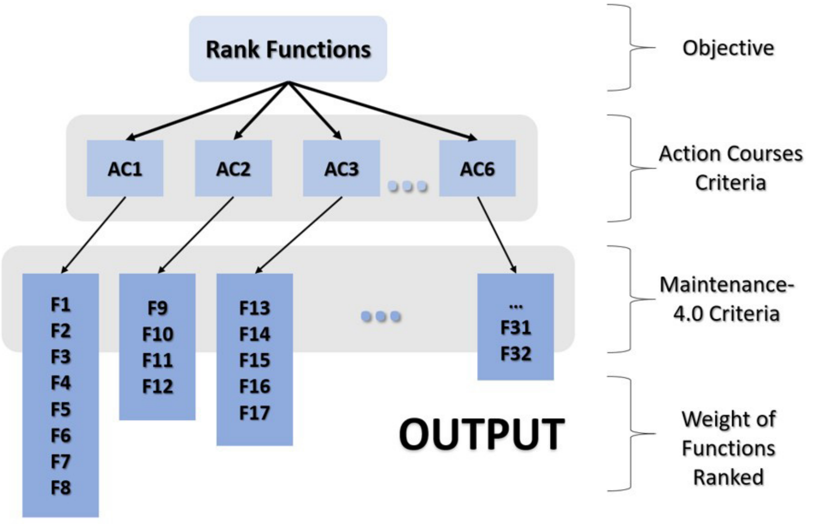

Figure 7. Step 02 – Maintenance-4.0 functions ranking (AHP model 2).

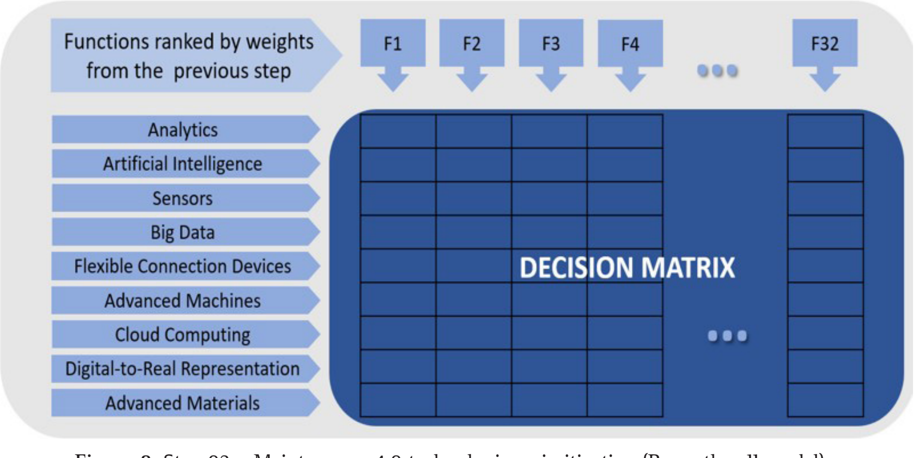

Figure 8. Step 03 – Maintenance-4.0 technologies prioritization (Promethee II model).

Specifically, the technologies suggested for implementation are intended to increase the maturity of legacy systems, at the same time, ensuring interoperability due to barriers applied to FEI/RAMI4.0 layers. After completing all the framework's stages, there will be enough information to develop an assertive I4.0 compliance plan. Such a plan suggests that: The Maintenance-4.0 technologies selected in Step 03 enable the functions prioritized in Step 02, which will act on the diagnosed areas arising from the Step 01 maturity assessment.

4. Discussions

To test the framework, a case study considered a multinational vehicle manufacturer. With a presence in more than 120 countries, the manufacturing complex in the southern region of Brazil employs approximately 8 thousand employees and has a production capacity of 320 thousand vehicles per year. We sought an area that offered a wider range of equipment, which is why the recently expanded engine factory (2019) has become the best option, mixing a wide range of modern and legacy machinery. Two engineers and one maintainer were participants in the assessments, answering the questionnaires from the first and second steps in an interviewed format.

4.1. Maturity assessment analysis results

In Step 01, the industrial maturity assessment made with the AHP method (seen in Figure 6) according to the maintenance managers' questionnaire represented in Figure 9 resulted in the analysis from Figure 10.

In order to clarify any possible doubts regarding the questionnaire, one of the authors followed the professionals' considerations in person without any interference that was not requested. All the Consistency ratio of each layer comparison were accepted for being below 10%: Asset: 0.08380; Business: 0.05787; Communication: 0.09363; Functional: 0.06948; Information: 0.05362; Integration: 0.04954.

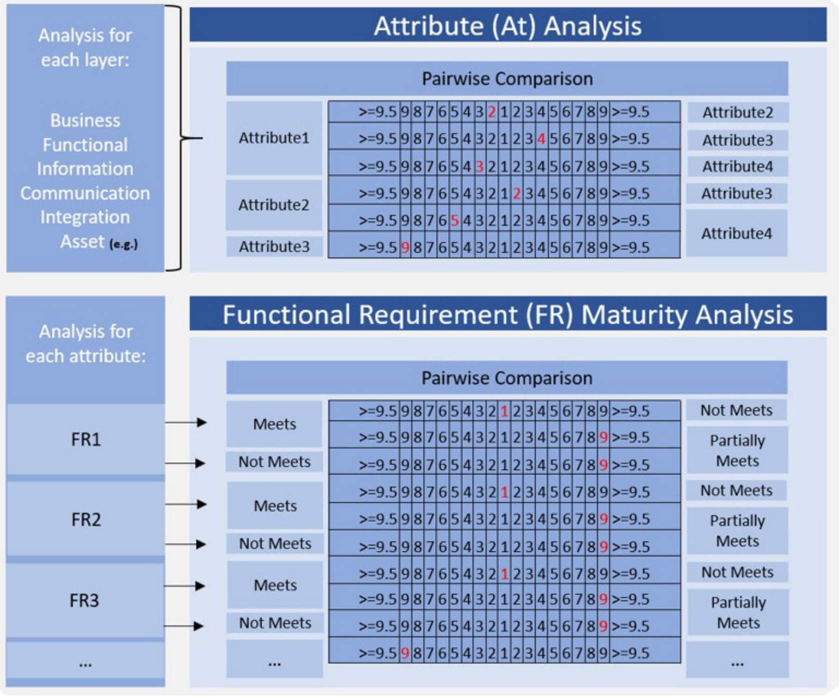

Figure 9. Maturity *questionnaire* (Step 01) example.

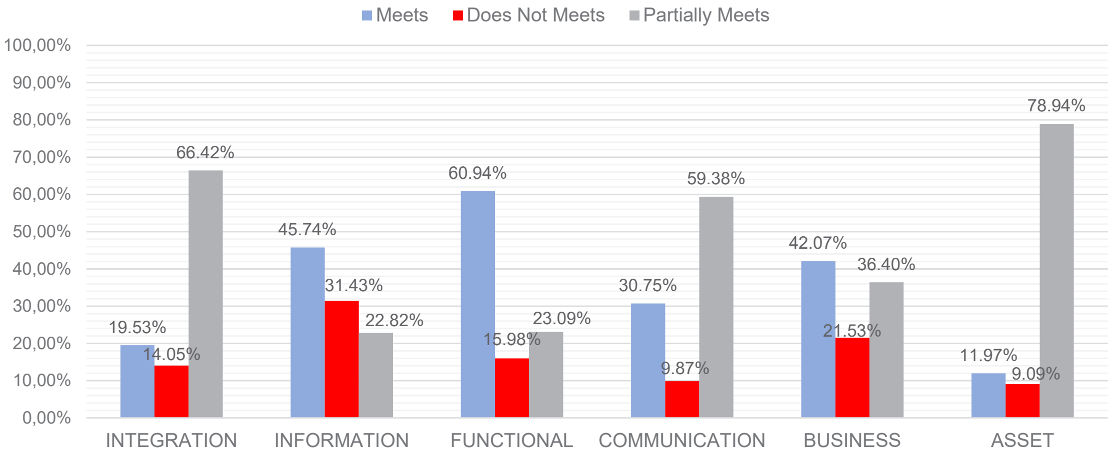

Figure 10. RAMI 4.0 layers' interoperability assessment from Step 01.

For the Asset layer, the maintenance professional highlights the functional requirement "Supervise equipment performance" and in the Business layer "Assist in an easy and quick way in individual decision making". The functional requirement in Communication layer "Allow connection and exchange of information on mobile devices" and in the Functional layer "Record failure prediction learning based on maintenance history" were highlighted. In the Information layer was highlighted "Ensure data storage capacity" functional requirement and finally, the Integration layer stands out the "Allow the ability to connect with different industrial protocols" requirement.

With deeper analysis, even though Business and Information layers meet the level of maturity, in both cases the alternatives "does not meet" and "partially meets" together exceeds 50%. This means that the AHP method is pointing out the preference (i.e., acknowledgment) of decision-makers, that the factory is at a level that "meets" the requirements, but with more uncertainty in comparison with the Functional layer, for example. The analysis is presented in Appendix 1.

4.2. Functions prioritization analysis results

In Step 02, the functions of the Maintenance-4.0 model were ranked by relevance. A graph with the prioritization of its courses of action is presented in Figure 11.

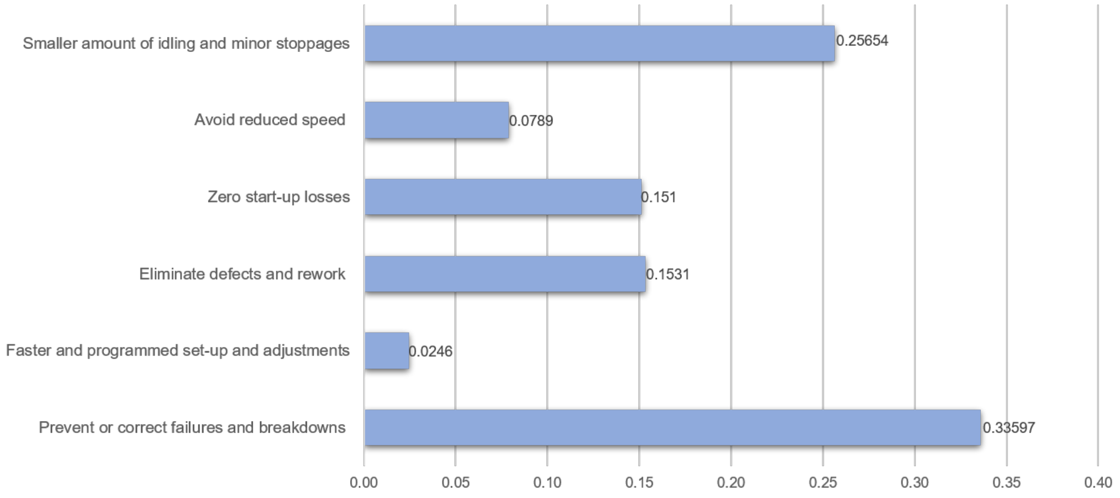

Figure 11. Maintenance-4.0 best courses of action.

The 32 maintenance functions are ordered according to their respective weight in Table 4, resulting from the normalization of the AHP method (seen in Figure 7). The overall course of action comparison was acceptable with a Consistency ratio: 0.04973.

The application of Step 02 took place in a second meeting, through a second questionnaire. A summary of the results obtained in Step 01 was made available to the maintainer, aiming to direct him to attribute less relevance to decisive maintenance functions poorly related to the target areas. The analysis is presented in Appendix 2.

4.3. Technologies prioritization analysis results

For Step 03, one of the authors played the role of decision-maker as a specialist/consultant. This was possible because of the knowledge acquired by the literature review on I4.0 technologies in the maintenance context. The weights of the functions obtained in Step 02 were imputed in the Promethee II method (seen in Figure 8). Then the alternatives, Maintenance-4.0 technology groups, were analyzed by their level of need i.e., syntactic graduation from 1 to 9. Table 5 presents the ranking of the most relevant technology groups to meet the Maintenance-4.0 functions. The *phi*, represents the preference index used by the method.

Table 4. Maintenance-4.0 Decisive Functions' Rank.

Decisive Maintenance-4.0 Functions	Weight
11) Corrective adjustment due to a faster and programmed set-up	64.77%
15) Predictive decision making to smaller amount of idling	62.06%
29) Startup planning to zero losses due to validation test	55.82%
20) Predictive decision making to avoid reduce speed	53.36%
25) Predictive decision making due to quality monitoring to eliminate defects	51.63%
05) Predictive maintenance due to predictive plan	32.91%
12) Corrective decision making to a faster set-up due to analysis	24.32%
30) Predictive decision making to zero start-up losses due to acquired data	23.90%
04) Inspection routine to prevent or correct failures	22.40%
24) Preventive decision making to eliminate rework	21.00%
18) Preventive decision making to avoid reduce speed due to KPIs	20.83%
07) Corrective maintenance to correct failures due to service execution	18.34%
14) Machine to machine communication due to report management	16.70%
19) Facility alignment to avoid reduce speed	14.19%
23) Cost optimization to eliminate defects and rework	12.29%
13) Preventive decision making for smaller amount of idling	11.73%
08) Corrective decision making to correct failures due to analysis	11.00%
28) Preventive decision making to less start-up losses due to system integration	10.22%
27) Corrective decision making to eliminate defects due to analysis	10.05%
22) Corrective decision making to avoid reduce speed due to analysis	7.22%
03) Preventive decision making to prevent failures and breakdowns	6.72%
32) Corrective decision making to zero start-up losses due to analysis	6.56%
17) Corrective decision making to a smaller amount of idling due to analysis	5.82%
09) Preventive decision making due to schedule	5.46%
10) Predictive decision making due to setting time	5.46%
26) Corrective maintenance to eliminate rework	5.03%
21) Corrective maintenance to avoid reduce speed due to service execution	4.40%
16) Corrective maintenance to less stoppage service	3.69%
01) Equipment upgrade to prevent failures	3.53%
31) Corrective maintenance to less start-up losses	3.50%
02) Improvement due to education and training	2.63%
06) Predictive decision making to prevent failures and breakdowns	2.49%

Table 5. Most relevant technologies analysis.

Rank	Technology	Method Relevance
1st	Analytics	Phi 0.4245
2nd	Artificial Intelligence	Phi 0.3455
3rd	Sensors	Phi 0.2342
4th	Big Data	Phi 0.1930
5th	Flexible Connection Devices	Phi 0.1713
6th	Advanced Machines	Phi 0.1566
7th	Cloud Computing	Phi -0.1923
8th	Digital-to-Real Representation	Phi -0.4994
9th	Advanced Materials	Phi -0.8334

Technologies at the cyber level were predominant: Analytics, Artificial Intelligence, and Big Data; along with Sensors at a physical level. They are responsible for enabling actions that are lacking in the factory, as established in Step 02.

4.4. Summarizing

The results of the framework's application in an automobile factory show that it was possible to provide guidelines for adequacy plans. Although it has been positively validated, its complexity is evident. Among the main difficulties encountered are the long questionnaires that need to be filled out in the steps, as many judgments are necessary. However, it was confirmed that the proposed digital functionalities correspond with the organization's strategy of elevating efficiency and performance standards.

The purpose of the framework was to promote a new way of solving the application of technologies that support Industry 4.0 in legacy and maintenance systems. For that existing frameworks' concepts were used to define such a non-trivial digital transformation strategy. It contributes in three distinct points, defining maintenance in I4.0; relating system's adaptation and interoperability; and, how MCDM organize problems, supporting subjective decisions encountered in digital transformation projects.

5. Conclusions and future works

The research developed here sought to answer the following question: "How to define a technology prioritization plan in order to adapt legacy systems for Industry 4.0 requirements?". This need is part of the increasing demand for adaptation to I4.0, where the reconditioning of legacy systems becomes the objective of organizations that seek to assign new functionalities to their equipment through modernization processes. With the research question in mind, a three steps framework was built. Multicriteria decision-making methods (AHP and Promethee II) encapsulated this framework, giving a tooling bias to it. Based on the similarities of RAMI4.0 and FEI architectures, Step 01 proposes a maturity analysis As-is in the perspective of Industry 4.0 and highlighting the analyzed system's interoperability barriers. Thereafter, Step 02 proposes a To-be vision of the functions encountered in a maintenance system that operates in the context of I4.0 (Maintenance-4.0 architecture). Finally, Step 03 proposes I4.0 technologies uncovered in maintenance applications. Our results have proven that such a framework will make it possible to elaborate more assertive guidelines, capable of aligning legacy maintenance systems with the vision of highly interoperable manufacture, necessary to fully access the benefits brought by Industry 4.0.

As future work, another initiative proposing different approaches for the framework's steps are also being tested. Firstly, to understand if it is feasible to optimize the legacy system in the first place. Secondly, to solve only the most decisive Maintenance-4.0 functions. This initiative could reduce the framework complexity focusing on important functions only. Further, it could be applied more than once, highlighting new decisive functions each time the previous ones were implemented, similar to a bottleneck analysis. This could support a gradual digital transformation.

As a final consideration, the digitalization of information, processes, functions that make up the operations of a business, and business strategies are necessary but not enough to achieve excellence. Most importantly, digitalization is essentially about technology, but digital transformation is not. Therefore, this work emphasizes that analogous with the empower of people with decision support tools, digital transformation is about people. It is how to improve the quality of people's lives at work and how to improve the performance of organizations for people, both developers and customers of the final product.

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Appendix 1. Step 01 AHP – Interviews' geometric mean.

Attribute									Assignment of Values											Attribute
Assessment of Relevance of Attributes to the Asset Layer																				
Reliability in the Acquisition of Data	>=9.5	9	8	7	6	5	4	3	2*	1	2	3	4	5	6	7	8	9	>=9.5	Identify Functional Faults
	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Equipment Healthy
	>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Telemetry
Identify Functional Faults	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	Equipment Healthy
	>=9.5	9	8	7	6	5*	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Telemetry
Equipment Healthy	>=9.5	9*	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Telemetry
Assessment of Relevance of Attributes to the Business Layer																				
Attribute									**Assignment of Values**											**Attribute**
Costs	>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Availability
	>=9.5	9	8	7	6	5	4	3	2	1*	2	3	4	5	6	7	8	9	>=9.5	Resources
	>=9.5	9	8	7	6	5	4	3	2	1	2	3*	4	5	6	7	8	9	>=9.5	Decision Making
Availability	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Resources
	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Decision Making
Resources	>=9.5	9	8	7	6	5	4	3	2	1	2	3*	4	5	6	7	8	9	>=9.5	Decision Making
Assessment of Relevance of Attributes to the Communication Layer																				
Attribute									**Assignment of Values**											**Attribute**
Scalability	>=9.5	9	8	7	6	5	4	3	2*	1	2	3	4	5	6	7	8	9	>=9.5	Heterogeneity of Data Sources
	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5*	6	7	8	9	>=9.5	Mobility
	>=9.5	9	8	7	6	5	4	3	2	1	2	3*	4	5	6	7	8	9	>=9.5	Security and Privacy
Heterogeneity of Data Sources	>=9.5	9	8	7	6	5	4	3	2	1	2	3*	4	5	6	7	8	9	>=9.5	Mobility
	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Security and Privacy
Mobility	>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Security and Privacy
Assessment of Relevance of Attributes to the Functional Layer																				
Attribute									**Assignment of Values**											**Attribute**
Diagnosis	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	Efficiency
	>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Intelligence
	>=9.5	9	8	7	6	5	4	3	2*	1	2	3	4	5	6	7	8	9	>=9.5	Results View
Efficiency	>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Intelligence
	>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Results View
Intelligence	>=9.5	9	8	7	6	5	4	3	2	1	2	3*	4	5	6	7	8	9	>=9.5	Results View
Assessment of Relevance of Attributes to the Information Layer																				
Attribute									**Assignment of Values**											**Attribute**
Data Fusion	>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Utility
	>=9.5	9	8	7	6	5	4	3	2*	1	2	3	4	5	6	7	8	9	>=9.5	Variety
	>=9.5	9	8	7	6	5	4	3	2*	1	2	3	4	5	6	7	8	9	>=9.5	Speed
	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	Volume
Utility	>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Variety
	>=9.5	9	8	7	6	5	4	3	2*	1	2	3	4	5	6	7	8	9	>=9.5	Speed
	>=9.5	9	8	7	6	5	4	3	2	1	2	3*	4	5	6	7	8	9	>=9.5	Volume
Variety	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	Speed
	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Volume
Speed	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Volume
Assessment of Relevance of Attributes to the Integration Layer																				
Attribute									**Assignment of Values**											**Attribute**
Connectivity	>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Flexibility
	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	Interoperability
	>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Security/ Stability
Flexibility	>=9.5	9	8	7	6	5	4	3	2	1	2	3*	4	5	6	7	8	9	>=9.5	Interoperability
	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	Security/ Stability
Interoperability	>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Security/ Stability

Appendix 2. Step 02 AHP – Interviews' geometric mean. The symbol (*) represent the criterion weight.

Assessment of Relevance Between the Sub-Criteria																					
Criterion	Sub-Criteria	Assignment of Values																			Sub-Criteria
Faster and Schedule Settings and Adjustments	Preventive Decision Making Due to Schedule	>=9.5	9	8	7	6	5	4	3	2	1*	2	3	4	5	6	7	8	9	>=9.5	Predictive Decision Making Due to Setup Time
		>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8*	9	>=9.5	Corrective Adjust Due to Faster and Schedule Setup
		>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6*	7	8	9	>=9.5	Corrective Decision Making for Faster Setup Due to Analysis
	Preventive Decision Making Due to Setup Time	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8*	9	>=9.5	Corrective Adjustment Due to Faster and Schedule Setup
		>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6*	7	8	9	>=9.5	Corrective Decision Making for Faster Setup Due to Analysis
	Corrective Adjustment Due to Faster Schedule Setup	>=9.5	9	8	7	6	5*	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	
Eliminate Defects and Rework	Cost Optimization to Eliminate Defects and Rework	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	Preventive Decision Making to Eliminate Rework
		>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8*	9	>=9.5	Predictive Decision Making Due to Quality Monitoring to Eliminate Defects
		>=9.5	9	8	7	6	5*	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Eliminate Rework
		>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Eliminate Defects by Analysis
	Preventive Decision Making to Eliminate Rework	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7*	8	9	>=9.5	Predictive Decision Making Due to Quality Monitoring to Eliminate Defects
		>=9.5	9	8	7	6	5*	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Eliminate Rework
		>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Eliminate Defects by Analysis
	Predictive Decision Making Due to Quality Monitoring to Eliminate Defects	>=9.5	9	8*	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Eliminate Rework
		>=9.5	9	8	7	6*	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Eliminate Defects by Analysis
	Corrective Maintenance to Eliminate Rework	>=9.5	9	8	7	6	5	4	3	2	1	*2	3	4	5	6	7	8	9	>=9.5	
Avoid Speed Reduction	Preventive Decision Making to Avoid Slowing Down Due to KPIs	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	Installation Alignment to Avoid Slowing Down
		>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6*	7	8	9	>=9.5	Predictive Decision Making to Avoid Slowing Down
		>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Avoid Slowing Down Due to Execution of the Service
		>=9.5	9	8	7	6	5	4	3	2*	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Avoid Slowing Down Due to Analysis
	Installation Nesting to Avoid Reducing Speed	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Predictive Decision Making to Avoid Slowing Down
		>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Avoid Slowing Down Due to Execution of the Service
		>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Avoid Slowing Down Due to Analysis
	Predictive Decision Making to Avoid Slowing Down	>=9.5	9	8	7	6*	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Avoid Slowing Down Due to Execution of the Service
		>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Avoid Slowing Down Due to Analysis
	Corrective Maintenance to Avoid Slowing Down Due to Execution of the Service	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	

Appendix 2. Continued...

Assessment of Relevance Between the Sub-Criteria																					
Criterion	Sub-Criteria	Assignment of Values																			Sub-Criteria
Lesser Quantities of Downtimes and Small Stops	Preventive Decision Making for Less Idle Amount	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6*	7	8	9	>=9.5	Machine to Machine Communication Due to Report Management
		>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Predictive Decision Making for Less Amount of Downtime
		>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Reduce Downtime Service
		>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Reduce Downtime Due to Analysis
	Machine to Machine Communication Due to Report Management	>=9.5	9	8	7	6	5*	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Predictive Decision Making for Less Amount of Downtime
		>=9.5	9	8*	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Reduce Downtime Service
		>=9.5	9	8	7	6*	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Reduce Downtime Due to Analysis
	Predictive Decision Making for Less Amount of Downtime	>=9.5	9	8*	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Reduce Downtime Service
		>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Reduce Downtime Due to Analysis
	Corrective Maintenance to Reduce Downtime Service	>=9.5	9	8	7	6	5	4	3	2	1	2	3*	4	5	6	7	8	9	>=9.5	
Zero Starts Stops	Preventive Decision Making to Reduce Departure Losses Due to System Integration	>=9.5	9	8	7	6	5	4	3	2*	1	2	3	4	5	6	7	8	9	>=9.5	Initial Planning for Zero Losses Due to Validation Testing
		>=9.5	9	8	7	6	5	4	3	2	1	2	3	4	5	6*	7	8	9	>=9.5	Predictive Decision Making for Zero Departure Losses Due to Acquired Data
		>=9.5	9	8	7	6*	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Reduce Departure Losses
		>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Zero Initial Losses Due to Analysis
	Initial Planning for Zero Losses Due to Validation Testing	>=9.5	9	8	7	6	5	4	3	2	1	2	3	4*	5	6	7	8	9	>=9.5	Predictive Decision Making for Zero Departure Losses Due to Acquired Data
		>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Reduce Departure Losses
		>=9.5	9	8	7	6	5	4	3*	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Zero Initial Losses Due to Analysis
	Predictive Decision Making for Zero Departure Losses Due to Acquired Data	>=9.5	9	8	7	6*	5	4	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Maintenance to Reduce Departure Losses
		>=9.5	9	8	7	6	5	4*	3	2	1	2	3	4	5	6	7	8	9	>=9.5	Corrective Decision Making to Zero Initial Losses Due to Analysis
	Corrective Maintenance to Reduce Departure Losses	>=9.5	9	8	7	6	5	4	3	2	1	2*	3	4	5	6	7	8	9	>=9.5	